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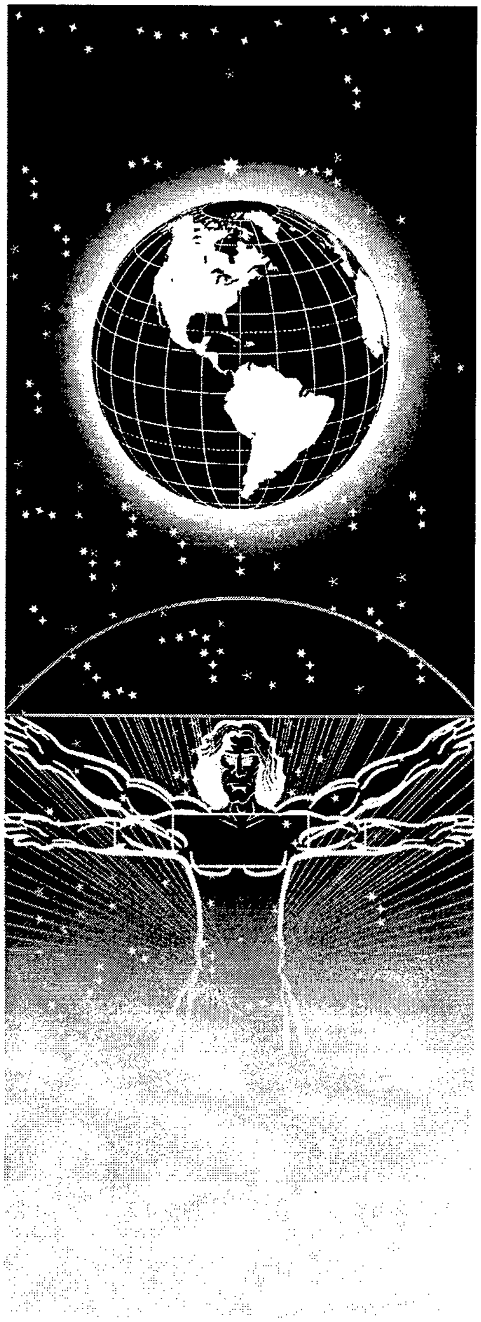

UNITED STATES AIR FORCE
ARMSTRONG LABORATORY

A Bayesian Classifier Based on a Deterministic Annealing Neural Network for Aircraft Fault Classification

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A Bayesian classifier based on a recurrent neural network was developed for aircraft fault classification. From historical maintenance data, the posterior probabilities of fault classification based on given fault indicators are estimated and derived using the Bayes' rule. Based on Bayesian decision theory, the fault classification problem is formulated as a linear integer programming problem to minimize an expected loss function using the posterior probabilities. The linear integer programming problem is then converted equivalently to a standard linear programming problem. A two-layer recurrent neural network is used to carry out the computation task for fault classification by solving the formulated linear programming problem. The simulation results of a pilot study based on the synthetic data on the fire control radar system in F-16 aircraft show that the neural network approach is capable of real-time aircraft fault classification.

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LIST OF ABBREVIATIONS

AL/HRG	Armstrong Laboratory/ Logistics Research Division
AFOSR	Air Force Office of Scientific Research
IMIS	Integrated Maintenance Information System
BCS	Bench Check Serviceable
LRU	Line Replaceable Unit
SRU	Shop Replaceable Unit
MFL	Maintenance Fault List

PREFACE

The work described in this paper was performed by Dr. Jun Wang of the University of North Dakota and Mr. Shing P. Chu of the U. S. Air Force, Armstrong Laboratory, Logistics Research Division (AL/HRG). This effort was conducted under The Air Force Office of Scientific Research (AFOSR), Summer Faculty Research Program, contract number: F49620-93-C-0063.

SUMMARY

In recent years, several techniques have been developed to create "intelligent" diagnostic aiding systems. Most of these systems, including the current Integrated Maintenance Information System (IMIS) diagnostic module, involve modeling the systems to be maintained. These systems have the disadvantage of requiring extensive efforts to develop them. A developing technology, neural networks, provides a promising alternative. Neural nets develop diagnostic strategies by learning from past experience with the system, and do not require extensive modeling. Neural networks are well suited to diagnostic applications.

This paper presents:

- An aircraft diagnostic problem formulated as mathematical descriptions.

- A detailed description of constraint construction.

- An explanation of a recurrent neural network architecture and its construction.

- Simulation result.

I. ABSTRACT

A Bayesian classifier based on a recurrent neural network was developed for aircraft fault classification. From historical maintenance data, the posterior probabilities of fault classification based on given fault indicators are estimated and derived using the Bayes' rule. Based on Bayesian decision theory, the fault classification problem is formulated as a linear integer programming problem to minimize an expected loss function using the posterior probabilities. The linear integer programming problem is then converted equivalently to a standard linear programming problem. A two-layer recurrent neural network is used to carry out the computation task for fault classification by solving the formulated linear programming problem. The simulation results of a pilot study based on the synthetic data on the fire control radar system in F-16 aircraft show that the neural network approach is capable of real-time aircraft fault classification.

II. INTRODUCTION

An aircraft is a complex electromechanical system composed of thousands of parts. Because of the complexity, aircraft fault diagnosis and classification are challenging tasks, especially for military aircraft for which the cost and time are considered. The traditional diagnostic methods for aircraft maintenance using technical manuals are costly to author and often fail to isolate the cause of the aircraft failure, thus impacting mission readiness and increasing maintenance costs. High field maintenance hours are often caused by incorrect diagnoses and subsequent false removals. In addition, historical information from Maintenance Data Collection Systems is difficult to access and rarely used. Each of these factors contribute to the need for a diagnostic system that is capable of learning from historical data in order to identify the faulty units and correctly predict the nature of faults. Artificial neural networks provide a possible solution to the fault classification problem.

Resembling biological nerve systems more or less in structure, neural networks are parallel distributed models composed of many simple processing elements. In processing information, these elements operate concurrently and collectively. During the past ten years, neural networks for pattern classification have been one of the most active areas in intelligent systems research and various neural network models have been developed for pattern classification (Specht, 1990). The results of numerous studies have shown the superior performance of neural networks for pattern classification.

In this paper, a two-layer recurrent neural network is presented for aircraft fault classification. The background information about the aircraft fault classification is given in Section III. Based on the Bayesian decision theory, the aircraft fault classification problem is formulated as a linear integer programming problem and then converted to a linear programming problem in Section IV. The energy function, dynamical equation, and architecture of the recurrent neural network are discussed in Section V. The simulation result of a pilot study for fault classification of F-16 radar systems are presented in Section VI. Finally, conclusions are presented in Section VII.

III. BACKGROUND

A bench check serviceable (BCS) occurs when the reported faulty component checks good when tested in the back shop. BCS occurs at the maintenance shop level and is always the result of unnecessary removal of LRU. Early knowledge that an LRU has a history of frequent BCSs and is likely to BCS can help the maintenance technician to modify his diagnostic procedures, thus reducing unnecessary removal of LRU's. A well-trained technician can tell from the maintenance history of the LRU whether it is likely to BCS, thus providing this project with a set of sample data. This report presents a process for developing a practical fault classifier that uses neural network technology and historical data to identify faults in today's military aircraft systems.

IV. PROBLEM FORMULATION

To facilitate the ensuing explanation, let the numbers of part units, fault categories, and fault indicators be denoted as m, n, and p, respectively. Let x_{ij} be denoted as the decision variable defined as follows: for $i = 1, 2, ..., m, j = 1, 2, ..., n$; where $x_{ij} = 1$ for part unit i belongs to fault category j and zero otherwise.

From past data, one can estimate the prior probability of each part unit (e.g., LRU, SRU) belonging to each category and the conditional probability of each fault indicator (e.g., MFL) for any part unit belonging to any category. From past data or the prior and conditional probabilities using the Bayes' rule, we can obtain the posterior probability of each part unit belonging to each category given any fault indicator. The prior probabilities form an m by n matrix. The conditional and posterior probabilities form two m by n by p three-dimensional data arrays.

For each misclassification, there is always some associated cost penalizing the mistake. The cost can be in terms of dollar amount, time wasted, or a combination of these factors, e.g.,

$$l_{ij} = w_1 C_{ij} + w_2 T_{ij} ,$$

where l_{ij}, C_{ij}, and T_{ij} are respectively the loss, cost, and time resulting from misclassification of part unit i in fault category j; w_1 and w_2 are weighted parameters to balance the cost and time criteria. In one extreme case where the maintenance time is the dominant criterion (usually in war time), $w_1 = 0$. In the other extreme case where the maintenance cost is the dominant criterion (usually in peace time), $w_2 = 0$. The cost coefficients form an m by n cost coefficient matrix.

Given a fault indicator, the sum of the Schur product of the loss coefficient matrix and the posterior probability matrix corresponding to the fault indicator constitutes the expected cost (loss) function. By minimizing the expected loss function subject to some feasibility constraints, faults can be classified.

One fundamental feasibility constraint that ensures an LRU can be assigned to only one class is as follows: $\sum_{j=1}^{n} x_{ij} = 1$, $i = 1, 2, ..., m$.

Given limited resources for expenditure and manpower, another feasibility constraint can be added: $\sum_{i=1}^{m} x_{ij} \le \mu_j$, for $i=1,2,\dots,n$; where $\mu_j \in \{0, 1, 2, \dots, m\}$ is the upper bound of numbers of part units allowed in category j. These upper bounds allow one to control the classification. They can be determined based on prior information on the size of the categories or the maintenance capacity of the workforce.

The last fundamental constraint is the integrity constraint defining the binary nature of the decision variables: $x_{ij} \in \{0, 1\}$.

In summary, the fault classification problem can be formulated as the following linear programming problem: For a given MFL_k, $k = 1, 2, \dots, p$;

maximize $\sum_{i=1}^{m}\sum_{j=1}^{n} P_{ijk}\, l_{ij} x_{ij}$;

subject to $\sum_{j=1}^{n} x_{ij} = 1, \qquad i = 1, 2, \dots m; \qquad (1)$

$\sum_{i=1}^{m} x_{ij} \le \mu_j, \qquad j = 1, 2, \dots, n; \qquad (2)$

$x \in \{0, 1\}; \qquad (3)$

where $l_{ij} = w_1 C_{ij} + w_2 T_{ij}$.

The inequality constraint (2) can be easily converted to an equality constraint by adding a slack variable y_j in for each j. Because the coefficients of the constraints (1) and (2) have the total unimodular property (Wang, 1994), the integrity constraint can be replaced with the non-negativity constraint. The above linear integer programming problem can thus be reformulated as the following linear programming problem: Given an MFL_k, $k = 1, 2, \dots, p$;

maximize $\sum_{i=1}^{m}\sum_{j=1}^{n} P_{ijk}\, l_{ijk} x_{ij}$; $\qquad (4)$

subject to $\sum_{j=1}^{n} x_{ij} = 1, \qquad i = 1, 2, \dots, m; \qquad (5)$

$$\sum_{i=1}^{m} x_{ij} + \mu_j y_j = \mu_j , \qquad j = 1, 2, ..., n; \tag{6}$$

$$x_{ij} \geq 0 ,\ y_j \geq 0 , i = 1, 2, ..., m;\ j = 1, 2, ..., n. \tag{7}$$

Note that constraints (5-7) together imply $x_{ij} \leq 1$ and $y_j \leq 1$.

V. DYNAMICAL EQUATION

To solve the optimization problem, a two-layer recurrent neural network is developed tailored from the deterministic annealing neural network for convex programming (Wang, 1994). Based on the formulated linear programming problem (4-7), a computational energy function can be defined as follows:

$$E(x,y,t) = \frac{1}{2}\sum_{i=1}^{m}\left(\sum_{j=1}^{n} x_{ij} - 1\right)^2 + \frac{1}{2}\sum_{j=1}^{n}\left(\sum_{i=1}^{m} x_{ij} + \mu_j(y_j - 1)\right)^2 - \sum_{i=1}^{m}\sum_{j=1}^{n} P_{ijk}\, l_{ijk}\, x_{ij} e^{-\eta t},$$

For simplicity, the same symbols are used hereafter to denote decision/slack variables and corresponding state variables.

The dynamical equation of a deterministic annealing neural network can be defined as a gradient system based on the energy function:

$$\frac{du_{ij}}{dt} = -\frac{\partial E(x,y,t)}{\partial x_{ij}}, \quad \frac{dv_j}{dt} = -\frac{\partial E(x,y,t)}{\partial y_j}.$$

Specifically, the dynamical equation of the neural network is shown as follows:

$$\frac{du_{ij}}{dt} = -\sum_{j=1}^{n} x_{ij} - \sum_{i=1}^{m} x_{ij} - \mu_j y_j + 1 + \mu_j + P_{ijk}\, l_{ijk}\, e^{-\eta t},$$

$$\frac{dv_j}{dt} = -\mu_j \sum_{i=1}^{m} x_{ij} - \mu_j^2 y_j + \mu_j^2 .$$

The standard unipolar sigmoid activation function is used:

$$x_{ij} = g(u_{ij}) = \frac{1}{1 + e^{-\xi u_{ij}}},\ y_j = g(v_j) = \frac{1}{1 + e^{-\xi v_j}};$$

where ξ is a scaling constant determining the sensitivity of activation.

The architecture of the two-layer neural network is shown in Figure 1, where the state variables of output neurons and hidden neurons correspond to the decision variables x_{ij} and slack variables y_j, respectively.

Since $\frac{dx_{ij}}{dt} = \frac{dg(u_{ij})}{du_{ij}}\frac{du_{ij}}{dt}$, $\frac{dy_j}{dt} = \frac{dg(v_j)}{dv_j}\frac{dv_j}{dt}$, and $\frac{dg(z)}{dz} = \xi g(z)g(1-z)$, the dynamical equation can be rewritten without u_{ij} and v_j as follows: for $i=1,2,\ldots m; j=1,2,\ldots,n$;

$$\frac{dx_{ij}}{dt} = -\xi x_{ij}(1-x_{ij})\left(\sum_{j=1}^{n} x_{ij} + \sum_{i=1}^{m} x_{ij} + \mu_j y_j - 1 - \mu_j - P_{ijk}\, l_{ijk}\, e^{-\eta t}\right),$$

$$\frac{dy_j(t)}{dt} = -\xi \mu_j y_j(1-y_j)\left(\sum_{j=1}^{m} x_{ij} + \mu_j y_j - \mu_j\right).$$

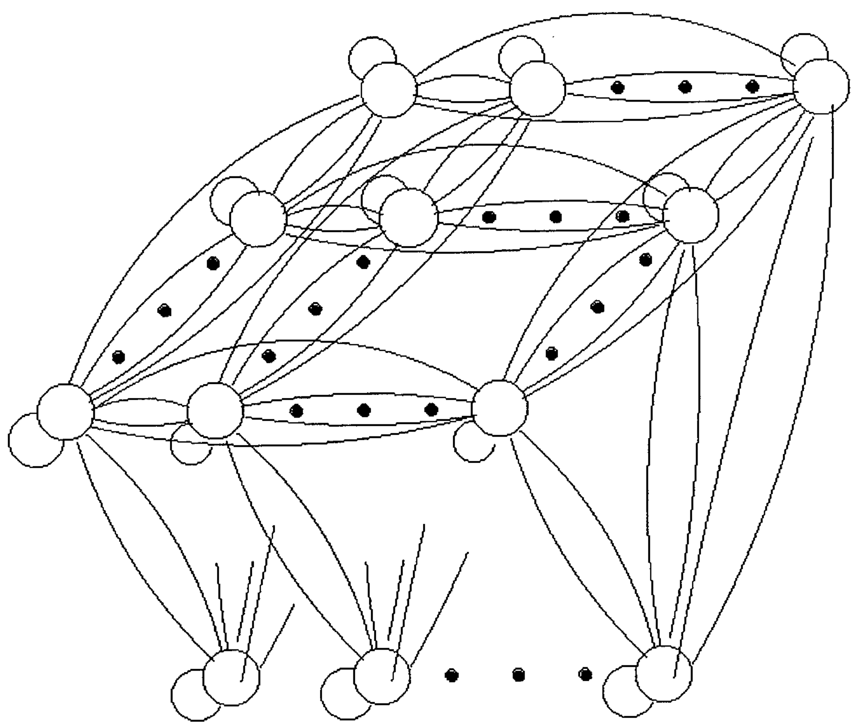

Figure 1. Two layers recurrent neural network.

VI. SIMULATION RESULT

While the proposed neural network approach can be used for general classification tasks with any numbers, patterns, categories, and evidence, this section discusses the simulation results of a specific pilot study. In this experiment, the task is to classify the line replaceable units into three categories: replaceable LRUs, repairable LRUs, and bench check serviceable LRUs. A bench check serviceable LRU is identified as the false removal of the LRU. A MATLAB program has been developed for simulating the recurrent neural network. The testing data was created to simulate the posterior probabilities and cost coefficients. The network was then tested with an arbitrary initial condition, $x_0 = 0.5*ones(8*3, 1)$. ξ and μ are selected to be 100 and 1, respectively. The result showed the network converged to the optimal solution that satisfied constraints (5-7) in about 500 iterations.

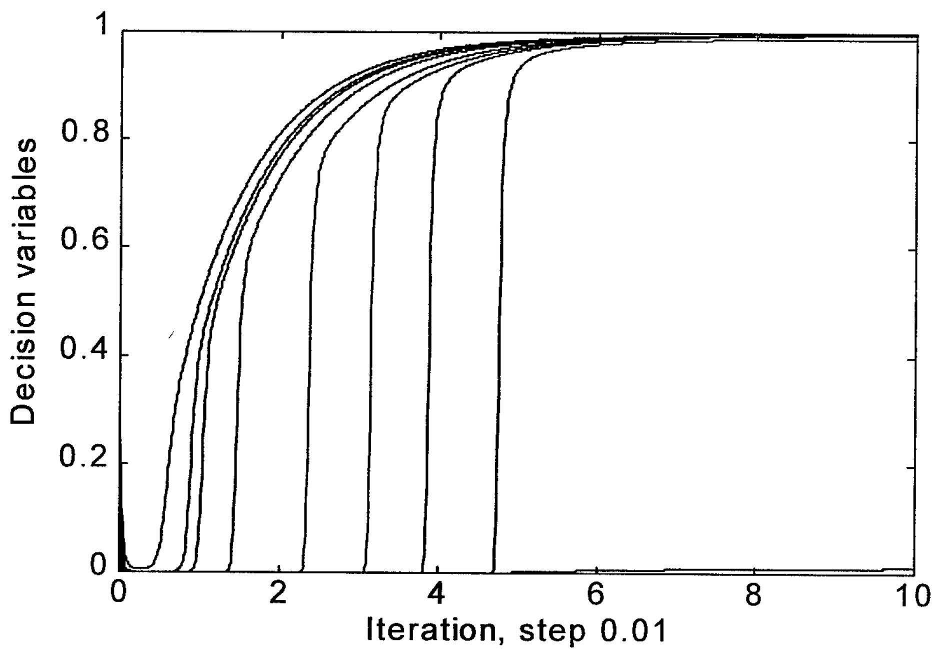

Figure 2. Simulation result.

VII. CONCLUDING REMARKS

A Bayesian classifier based on a recurrent neural network is developed for aircraft fault classification. The Bayesian classifier minimizes the expected loss, taking both maintenance cost and time into consideration. The proposed recurrent neural network provides a parallel computational model to carry out the optimization task. The proposed Bayesian classifier can serve as a core in a maintenance decision support system for aircraft diagnosis.

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